PLANETARY EXPLORATION AUTONOMOUS SCIENCE TARGET TOUCHABILITY EVALUATION USING A FUZZY RULE-BASED APPROACH

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ABSTRACT

With regards to Mars rover exploration, the ExoMars 2018 is the next ESA/Roscosmos mission. This is part of the Aurora programme with the future goal of returning rock samples to Earth as part of the Mars Sample Return (MSR) mission. Currently, science target selection, and whether or not it is possible for a robot arm to touch the target, is accomplished using human operators and scientists on Earth. The use of onboard autonomy would greatly reduce the human intervention, and it would be advantageous if the in-situ rover could evaluate autonomously if its robot arm could place an instrument against an identified science target. In this paper we propose a new approach to the problem of autonomous science target touchability evaluation. We assess the touchability of a potential science target in terms of its size (the number of pixels of the science target in the image), SV (SV is referred to as the science value of the science target), distance (the reachable distance of the arm between some minimum and maximum values; currently defined as near, medium, and far), and orientation (the angular regions of the arm's shoulder azimuth). We have identified that these science target attributes can be represented by fuzzy linguistic variables. We have divided the plane in front of the arm into the several partitions, which are ranked with the different touchability levels as a fuzzy-rule set. Currently the resultant fuzzy-rule base incorporates some 74 fuzzy rules. We have employed the MATLAB software architecture to implement our algorithm, and we have simulated various rock distributions to verify the validity and accuracy of our autonomous science target touchability evaluation approach.

Key words: Fuzzy logic; Touchability; Autonomous.

1. INTRODUCTION

Owing to the higher cost and risk of manned space exploration missions, space agencies primarily concentrate on unmanned planetary exploration. Therefore, a rover mission preferably selected provides direct and detailed surveys of the planetary terrain surface. Rover missions have been achieved on Mars and the Moon. However, technical challenges still remain for an exploration rover, and autonomy is the prime topic. There are two chief reasons for promoting autonomy, one of them is that planetary surface exploration is becoming increasingly constrained by uplink/downlink bandwidth, and another arises from the long radio propagation time in space. In the case of Mars for instance, it will be of the order of 40 minutes to receive and send one command, when the distance between the Earth and Mars is at a maximum. Hence, teleoperation using real time communication with a rover is not possible. Furthermore, communication capacity is restricted. Thus, for the efficient and effective investigation of the Mars environment an enhanced autonomy based approach is required.

The application of fuzzy logic in planetary exploration is currently one of the subject of studies. Recently, Seraji [7] proposed the construction of a so-called traversability index, which is meant to classify the difficulty a rover would encounter when attempting to traverse a region of terrain in a no priori knowledge environment. In the Seraji [7] paper, fuzzy logic is used to obtain the traversability index. Ayanna et al. [8] have presented an approach that combines the traversability map with a fuzzy map representation of traversal difficulty of the terrain into the path planning logic, and this approach concentrates on planning an optimally safe path of minimum traversal cost. Mahmoud [9] has utilized a fuzzy adaptation technique that examines the paths population throughout execution of the algorithm and adjusts operator probabilities to attain better solutions for path planning. Not only is fuzzy logic employed for the achievement of the traversability and path planning, but also it is applied to planetary landing and the tier-scalable robotic planetary reconnaissance. Navid [10] has addressed the issue of landing site selection using fuzzy rule-based reasoning. In this paper the score of each potential candidate landing site is obtained from sensor measurements that are feed into the fuzzy system to settle spatial and temporal dependence in the reasoning process. Furfaro et al. [11] have built a fuzzy system where the appropriate past/present water/energy indicators are able to be acquired when the tier-scalable mission framework is deployed, and have estimated habitability on Mars.

Currently, the most advanced exploration robots that have been deployed for planetary exploration are the Mars Exploration Rover (MER, "Spirit" and "Opportunity") and

the Mars Science Laboratory (MSL, "Curiosity"). However, they have the identical manipulation scenario consisting of four main stages for science target exploration. For the first stage, the rover transmits the images captured from the navigation camera to operators/scientists from Mars to Earth, and an interesting target is manually selected by scientists on Earth in a stereo range map. The 3D location of this target, the rover's goal distance from the target and subsequent operations for targeted driving uplinked as a command sequence are specified. For the second stage a target tracker enables the rover to autonomously drive to the goal position while avoiding obstacles, and to reach the goal position with the precision of a few centimeters. The scientists artificially designate the sampling point on the scientifical goal from the downlinked images in the third stage. In the last stage in order to sample and analyze the science target a variety of instruments on-board are utilized. For the first-stage of the entire operational scenario, Barnes et al. [4], and Pugh et al. [5], have proposed that a fuzzy rule based expert system (KSTIS 1.0) could be used. This system adopts knowledge elicitation from a planetary geologist to obtain the primary clues (*Structure*, *Texture* and *Composition*) as to the geological background of the rock, and eventually generates a useful science value score (SV) with respect to each rock in an image. In the second-stage, in order to determine whether the science goal can be acquired or not, both MER and MSL adopt a rigid approach using the robotic arm workspace. For instance, when it comes to the Curiosity rover then the workspace volume is an upright cylinder 80cm diameter, 100cm high, positioned 105cm in front of the front body of the rover when the rover is on a smooth flat terrain [12]. Therefore, the current strategy employed by MER and MSL is that the science target is deemed to be able to be acquired just when it is within the robotic arm workspace, which is a mechanical decision strategy. This strategy does not consider an extreme case where the interesting target is surrounded by the other rocks that can not be traversed in the '*rock garden*', and it is not able to get into the robotic arm workspace but it is just on the edge of workspace. However, the problem can be addressed when the robotic arm workspace is variable based on the distinct characteristic of the interesting target. Hence, we propose an autonomous flexible approach to adjust automatically the robotic arm workspace in terms of the science value score (SV) for the scientific goal. The strategy is capable of increasing properly the magnitude of the robotic arm workspace when the science value score is high.

The original contribution of this paper is the use of a Fuzzy Rule-based Reasoning (FRR) approach for constructing a model of target touchability, which is capable of evaluating the reachable probability of the arm relative to the rocks in the vicinity of the rover. For our work, we have extended the work of Pugh [5] for generating the science value score (SV) of each rock in the image. SV becomes a vital attribute of our system as an input parameter. We also have used a stereo vision servo system (AUPE-2) [2] as the main sensing modality to attain the other three attributes (*Size*, *Orientation* and *Distance*). Finally, the probability of the touchability combined with each rock in the image is generated.

The paper is organized as follows. In the next section a brief overview of the touchability system framework is discussed. Section 3 presents the building of the linguistic fuzzy sets together with the fuzzy rules associated with the respective attributes. The simulation experiment is reported and validates the proposed approach in Section 4. The paper is concluded with a brief review and future works are presented.

2. OVERVIEW OF THE TOUCHABILITY SYSTEM FRAMEWORK

This section introduces the structure of the proposed fuzzy logic based touchability system shown in Figure 1. The entire system is composed of six parts, which are the vision system, KSTIS 1.0, fuzzification, fuzzy inference engine, rule base and defuzzification. The inputs of the fuzzy logic controller are the outputs from the sensors of the vision system and KSTIS 1.0.

From previous research, the ability to autonomously detect and identify the scientifically interesting rocks and to accurately match and calculate the 3D location and the size of the targets, is provided from this system [1][3]. In the diagram the input data i_d, i_o, i_s obtained are the distance between arm base and the centroid of the target, the angular regions of the arm's shoulder azimuth, and the number of pixels of the science target in the image, respectively.

KSTIS 1.0 (the Knowledge based Science Target Identification System) aims at assisting in ground-based interpretation of scientific targets via making use of a fuzzy expert system [4][5]. This system is based on the *Structure, Texture* and *Composition* associated with scientific targets whose values are provided by scientists/experts on Earth, and i_{SV} is the score of *Science Value* from KSTIS 1.0.

The output signal o_t from the fuzzy controller is the touchability probability for the scientific targets.

3. THE PROPOSED APPROACH

The proposed fuzzy logic approach is uncomplicated, easy to comprehend, and provides a quick reaction capability. The fuzzy logic controller for the touchability system created adopts a typical structure that includes fuzzification, inference mechanism and defuzzification. In the following section these components are presented.

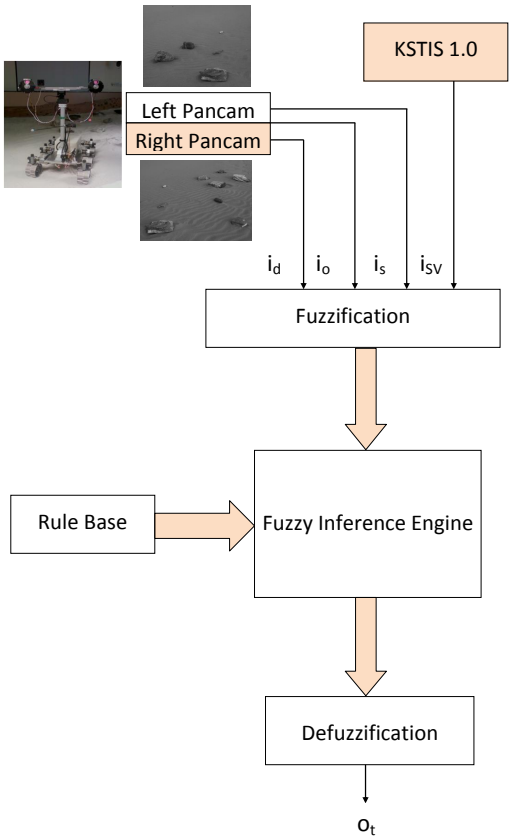

Figure 1. Fuzzy Logic Controller of the Touchability System.

3.1. Fuzzification

The fuzzification procedure maps the crisp input values to the linguistic fuzzy terms with membership function values between zero and one. In this section the four physical properties i.e., size, distance, orientation and SV are expressed by linguistic fuzzy sets as described below.

3.1.1. Size (i_s)

Cross-sectional area is charactered as the size of the object. Currently the typical way such as MER to identify surroundings is to form a detailed DEM by accomplishing stereo matching to the entire pixels in a pair of images. However in our study, in order to obtain the essential size information effectively just 5 points per object are applied for stereo matching (see Figure 2). In this figure the minimum rectangle (*A*,*B*,*C* and *D*) for each edge inscribes the leftmost, rightmost, uppermost and bottommost points (*H*,*F*,*E* and *G*) in the object, respectively, is provided for searching the stereo matching points. The point C is the cross point of the line segments 'EG' and 'HF' and is the centroid of the object. P1, P2, P3 and P4 represent the stereo matching points, whose three dimensional frame values are then derived by the external and internal parameters of the cameras.

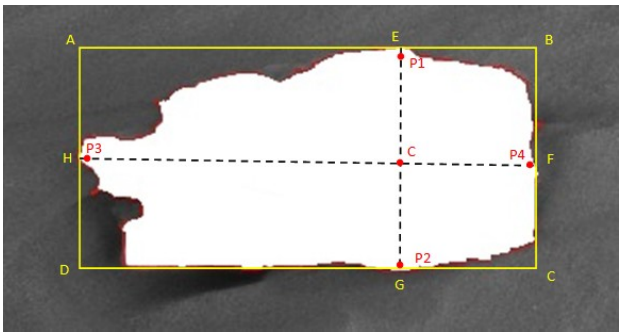

Figure 2. Stereo matching points selection.

The three linguistic fuzzy sets {SMALL, MEDIUM, BIG} are utilized to describe the size that is set up on the main five levels respectively. The levels are represented in Table 1. The membership function of these fuzzy sets are given in Figure 3.

Table 1. Membership function levels for Size.

Level No.	Small	Medium	Big	Area(cm^2)
0	1	0	0	<100
1.5	0.5	0.5	0	150
3	0	1	0	300
4.5	0	0.5	0.5	450
6	0	0	1	>600

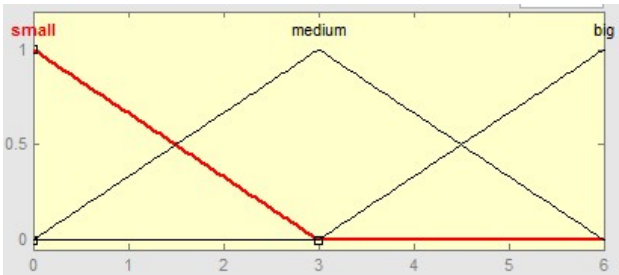

Figure 3. Membership function for the Size (i_s).

3.1.2. Distance (i_d)

The distance is a significant physical variable in our study, whose span is provided by the length of the robot arm. Here, we have employed the length of the Curiosity rover arm for our subsequent simulation experiments. The length of the Curiosity arm is 2.3 meters from the front of the rover body. In Figure 4, the distance is between the original point O in the mobile robot arm base frame seen and the centroid (C) of the object. The distance is represented by the three linguistic fuzzy sets {NEAR, MEDIUM, FAR}, which is set up on five levels respectively. The levels are represented in the Table 2. The membership function of these fuzzy sets are given in Figure 5.

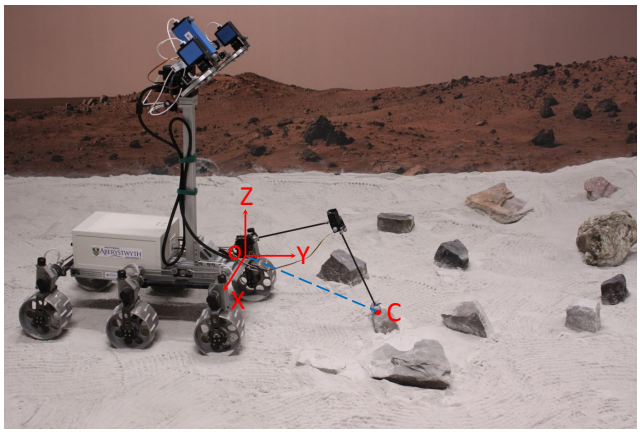

Figure 4. Distance between arm and object.

Table 2. Membership function levels for Distance.

Level No.	Near	Medium	Far	Distance(cm)
0	1	0	0	<60
1	0	0.5	0	105
2	0	1	0	145
3	0	0.5	0	185
4	0	0	1	230

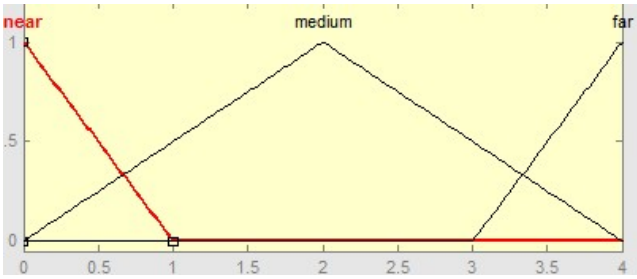

Figure 5. Membership function for the Distance (i_d).

3.1.3. Orientation (i_o)

The orientation is the angle formed by the straight line defined relative to the heading of the rover, and the straight line that connects the projection of the centroid of the object with the reference arm (see Figure 6). As shown in this figure, a transparent plane is a plane that is constituted by the X and Y axes. C' is the projection of C on the transparent plane. θ is an angle between the straight line OC' and Y axis, and is the orientation. In Figure 7, the orientation in front of the rover is divided into six regions that are represented by the six linguistic fuzzy sets {very-bad(VB), bad(B), very-soso(VS), soso(S), good(G), very-good(VG)}. The "very-good", "good", "soso", "very-soso", "bad" and "very-bad" are sectors at $\pm 15°$(Red), between $\pm 15°$ and $\pm 30°$(Turquoise), between $\pm 30°$ and $\pm 45°$(Yellow), between $\pm 45°$ and $\pm 60°$(Green), between $\pm 60°$ and $\pm 75°$(Orange), and between $\pm 75°$ and $\pm 90°$(Pink) relative to the heading of the rover, respectively. The membership functions of these sets are shown in Figure 8.

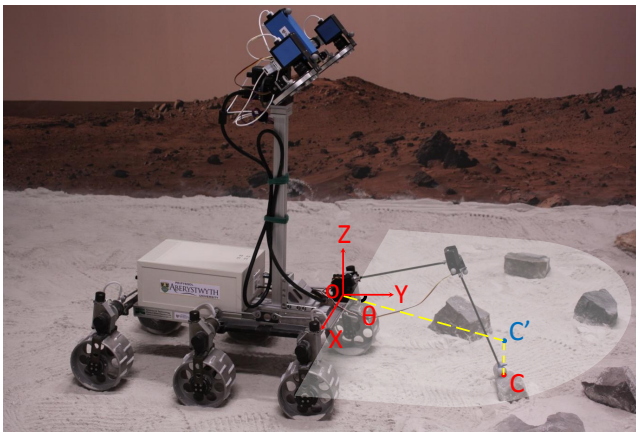

Figure 6. Orientation between arm and object.

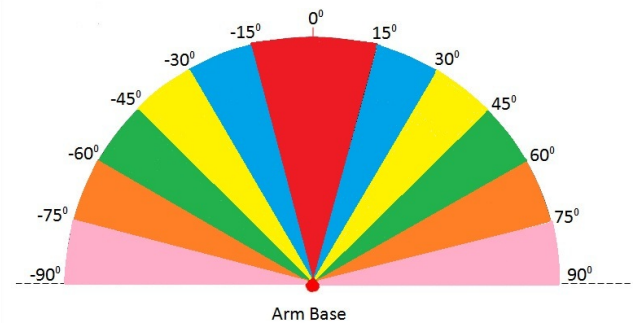

Figure 7. Decomposition of orientation regions.

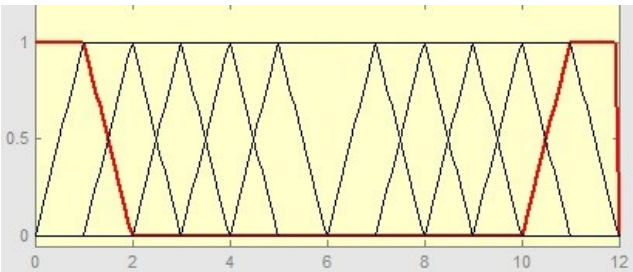

Figure 8. Membership function for the Orientation (i_o).

3.1.4. Science Value (SV) (i_{SV})

The science value (SV) is a score computed from KSTIS 1.0 system between 0 and 9999, which is represented by the three linguistic fuzzy sets {LOW, MEDIUM, HIGH}, which is set up on six levels respectively. The levels are shown in the Table 3. The membership function of these fuzzy sets are given in Figure 9.

3.2. Inference Mechanism

The inference mechanism is responsible for undertaking decision-making in the fuzzy logic controller using the reasoning, and achieving the two fundamental tasks: (1)

Table 3. Membership function levels for SV.

Level No.	Low	Medium	High	SV Score
0	1	0	0	<20
1	0.667	0	0	40
2	0.333	0	0	60
3	0	1	0	80
4	0	0	0.5	100
5	0	0	1	>120

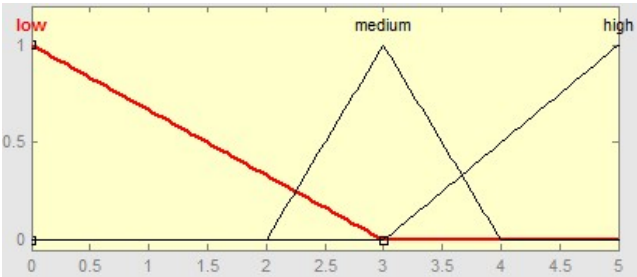

Figure 9. Membership function for SV (i_{SV}).

To determine the extent to which each rule is associated with the current situation as characterized by the inputs; and (2) To come to the conclusions utilizing the current inputs and the information in the rule base. Seventy-four rules have been combined with 72 rules shown in Figure 10 plus the two rules below for the proposed fuzzy controller.

- IF Size is SMALL THEN TIndex is VERYLOW
- IF SV is LOW THEN TIndex is VERYLOW

3.3. Defuzzification

The output of the fuzzy controller from the inference mechanism is mapped to a crisp value called *Touchability Index* by the defuzzification procedure. Currently, there are a number of methods provided for the defuzzification that transforms the conclusion of the inference mechanism into the subsequent output. Therefore defuzzification process is the opposite of the fuzzification. The "COG defuzzification" used combines the output represented by the implied fuzzy sets from all rules to calculate the gravity centroid of the possible distribution into a control action. The *Touchability Index* is represented by the seven linguistic fuzzy sets {VERYLOW, LOW, MEDIUMLOW, MEDIUM, MEDIUMHIGH, HIGH, VERYHIGH}. The membership function of these sets are shown in Figure 11, where the horizontal axis is the Touchability Index and the corresponding relative to the actual output is 0: 0%; 1: 10%; 2: $20\% \cdots 9 : 90\%; 10 : 100\%$.

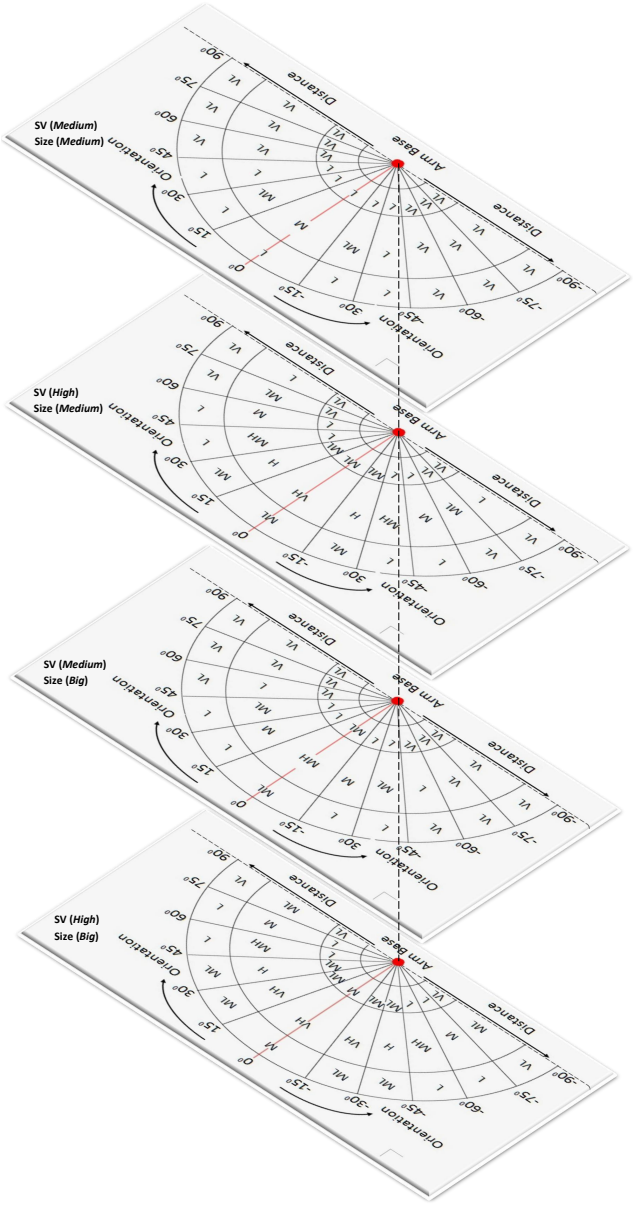

Figure 10. Rule base for touchability (VL-VeryLow, L-Low, ML-MediumLow, M-Medium, MH-MediumHigh, H-High, VH-VeryHigh).

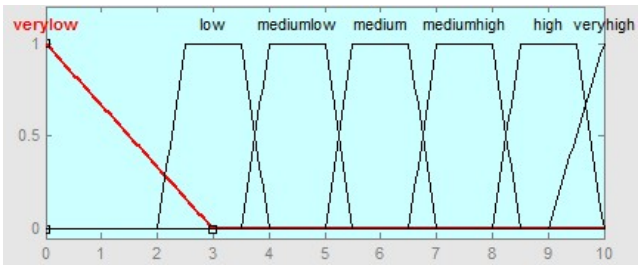

Figure 11. Membership function for Touchability Index (o_t).

4. SIMULATION RESULTS AND ANALYSIS

In the following simulation experiments we have constructed a data set to validate the fuzzy controller designed, and to work out the *Touchability Index* of the mock objects which are ranked by the *Touchability Index* and are compared with the manual rank by a human.

4.1. Comprehensive Simulation Experiment

Using the Microsoft Office Excel 2007 we have created a database for the rocks used for the simulation experiments (see Table 4), and have developed the fuzzy logic-based controller by defining fuzzy variables, fuzzy membership functions and rules utilizing the MATLAB Fuzzy ToolBox simulator. We have constructed nine rocks, in which three kinds of the rocks used, i.e. small (10×15), medium (20×15) and big (30×20). The three science value scores used are 45, 65 and 85. In Table 4, *Length* $\times$ *Width* is the size of the goal.

Table 4. Simulation experiment data.

Rock $NO.$	Length (cm)	Width (cm)	SV	Orientation (deg)	Distance (cm)
1	10	15	105	12	132
2	10	15	65	-65	166
3	10	15	35	50	111
4	20	15	105	-17	161
5	20	15	65	-33	126
6	20	15	35	72	151
7	30	20	105	5	148
8	30	20	65	32	167
9	30	20	35	-46	112

In order to better illustrate the science values (SV) rock ranking, we have designed a table where SV is represented by distinct colors (see Table 5).

Table 5. Correspondence between SV and colour.

Corresponding Colour	SV Scores
Cyan(c)	<20
Green(g)	20-39
Blue(b)	40-59
Yellow(y)	60-79
Magenta(m)	80-99
Red(r)	100-119
Black(k)	>120

We have designed a diagram to illustrate the rock ranking (see Figure 12). The centre of the frame is the arm base, the SV is represented by color, and the size of the rock is represented by the diameter of the color circle. We are able to intuitively rank the touchability sequence of these rocks, and the resultant human ranking is shown in the Artificial Rank column of Table 6. The numbers of the column TIndex are generated by running the designed fuzzy controller in MATLAB. The column *TRank* is a rank that is produced by the magnitude sequence of *TIdex* . We can see that the Artificial Rank is identical with the TIdex. Consequently, the results of the experiment demonstrate the validity of the proposed approach.

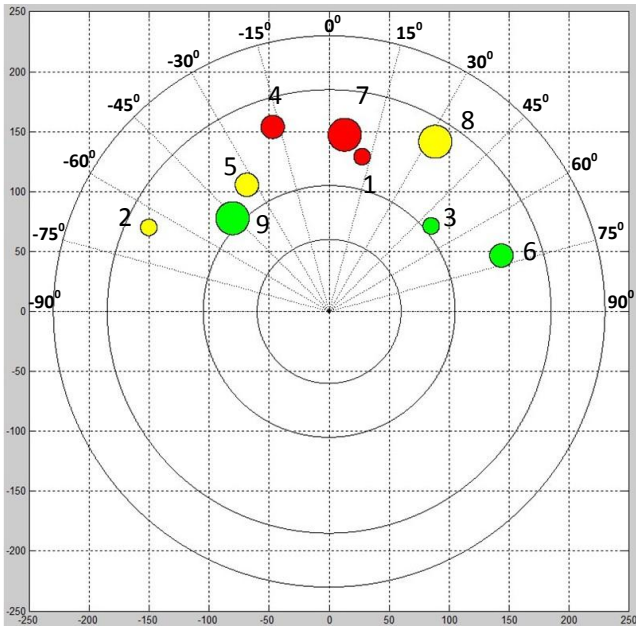

Figure 12. Simulated experiment environment.

Table 6. Simulation experiment result.

RockNO.	Artificial Rank	TIndex(%)	TRank
1	5	35.2	5
2	7	23.8	7
3	8	22.3	8
4	2	88.4	2
5	4	54.1	4
6	9	18.4	9
7	1	96.6	1
8	3	67.5	3
9	6	34.9	6

5. CONCLUSION AND FURTHER WORK

The fuzzy logic used have has two major benefits for the touchability system. First, the fuzzy rules are employed to emulate human experience for the acquisition of an object, which is readily intuitive and understandable. Second, because it is inevitable that the quality of the data for the SV and Size in measuring and interpreting is inaccurate, the tolerance of fuzzy logic to imprecision and uncertainty in sensor data is particularly appealing for our system.

In this paper, a fuzzy logic-based controller for the touchability of the science targets has been presented. The membership functions and fuzzy rules have been accomplished and the defuzzification has been carried out finally. Additionally, the simulation experiment has shown the validity of the proposed system within a MATLAB environment.

Without doubt, there still exists areas to be improved and enhanced. For example, it would be better to reduce the dimension of the *Orientation* fuzzy sets, which is in favour of the number of the fuzzy rules. Finally, we propose to move from simulation to real laboratory experiments with the PATLab 'Blodwen' half-scale ExoMars 2018 rover.

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REFERENCES

[1] Gui C., Barnes D., Pan L., 2012, A SIFT-Based Method for Matching Desired Keypoints on Mars Rock Targets, In the international Symposium on Artificial Intelligence, Robotics and Automation in Space (i-SAIRAS)

[2] Pugh S., Barnes D., Tyler L., et al., 2012, AUPE-A PanCam Emulator for the ExoMars 2018 Mission, In the international Symposium on Artificial Intelligence, Robotics and Automation in Space (i-SAIRAS)

[3] Gui C., Barnes D., Pan L., 2012, An Approach for Matching Desired Non-Feature Points on Mars Rock Targets Based on SIFT, In the Towards Autonomous Robotic System (TAROS) Conference

[4] Barnes D., Pugh S., Tyler L., 2009, Autonomous Science Target Identification and Acquisition (ASTIA) for Planetary Exploration, International Conference on Intelligent Robots and Systems, IEEE, St. Louis, USA, pp. 3329 - 3335

[5] Pugh S., 2009, Autonomous Science for Future Planetary Exploration Operations, PhD, thesis, Aberystwyth University

[6] Zadeh L., et al., 1996, Fuzzy Sets, Fuzzy Logic, Fuzzy Systems, Word Scientific Press, ISBN 9810224214

[7] Seraji H., 1999, Traversability Index: A New Concept for Planetary Rovers, Proceedings of the 1999 IEEE international Conference on Robotic and Automation

[8] Howard A., Seraji H.,Werger B., 2002, Fuzzy Terrain-Based Path Planning for Planetary Rovers, Proc. of the IEEE Int. Conf. on Fuzzy Systems, vol 1, May 2002, pp. 316-320

[9] Mahmound T., 2008, Hybrid intelligent path planning for articulated rovers in rough terrain, Fuzzy Sets and Systems, 159(21):2927-2937

[10] Navid S., Homayoun S., Landing Site Selection using Fuzzy Rule-Based Reasoning, International Conference on Robotics and Automation,IEEE, 4899-4904

[11] Furfaro R., et al., 2008, The Serach for Life Beyond Earth through Fuzzy Expert Systems, Planetary and Space Science

[12] Anderson R. C., Jandura L., Okon A. B., et al., 2012, Collecting Samples in Gale Crater, Mars; an Overview of the Mars Science Laboratory Sample Acquisition, Sample Processing and Handling System, Space Science Reviews